Predict Daily Life Stress based on Heart Rate Variability

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Abstract

The purpose of this study is to investigate the feasibility of predicting a daily mental stress level from analyzing *Heart Rate Variability* (HRV) by using a *Photoplethysmography* (PPG) sensor which is integrated in the wristband-type wearable device.

In this experiment, each participant was asked to measure their own PPG signals for 30 seconds, three times a day (at noon, 6 P.M, and 10 minutes before going to sleep) for a week. And 10 minutes before going to sleep, all participants were asked to self-evaluate their own daily mental stress level using *Perceived Stress Scale* (PSS). The recorded signals were transmitted and stored at each participant's smartphone via *Bluetooth Low Energy* (BLE) communication by own-made mobile application.

The preprocessing procedure was used to remove PPG signal artifacts in order to make better performance for detecting each pulse peak point at PPG signal. In this preprocessing, three-level-bandpass filtering which consisted three different pass band range bandpass filters was used.

In this study, frequency domain HRV analysis feature that the ratio of low-frequency (0.04Hz ~ 0.15Hz) to high-frequency (0.15Hz ~ 0.4Hz) power value was used. In frequency domain analysis, autoregressive (AR) model was used, because this model has higher resolution than that of *Fast Fourier Transform* (FFT).

The accuracy of this prediction was 86.35% on average of all participants. Prediction result was calculated from the leave-one-out validation.

The IoT home appliances are arranged according to the result of this prediction algorithm. This arrangement is offering optimized user's relaxation. Also, this algorithm can help acute stress disorder patients to concentrate on getting treatment.

1 Introduction

1.1 Introduction of stress

In a medical or biological term the definition of stress is a physical or psychological factor that increases mental or bodily tension. There are two factors in the sorts of stressors. One is external factor and the other is internal factor. External factors are from outside of our body, for example, from an environment, personal social situation, psychological anxiety, and so on. Internal factors are from inside of our body reaction, they can also increase stress, for example, illness or physical reaction from medication. This concept of definition is universally known as a '*Stimulus-based Stress*' defined by *Dr. Gillian Butler* [1]. And there is another term defined by *Dr. Gillian Butler* [1], which is called '*Response-based Stress*'.

The concept of '*Response-based Stress*' is based on *Hans Selye*'s book '*The Stress of Life*' [2], and paper [3]. Selye used the term of 'stress' for the first time and defined the *General Adaptation Syndrome* (GAS) which is the physical response to the stress with three stages. In the first stage, our body is alerted by stressor and responds to the alerts. Second stage is changing the balance of the *Autonomic Nervous System* (ANS), which consists of *Sympathetic Nervous System* (SNS) and *Parasympathetic Nervous System* (PNS), dealing with stress. The activity of ANS responses to the inverse relation with SNS and PNS [4]. SNS activity indicates the stress, exercise and heart disease. On the contrary, PNS activity primarily responses to the internal organs' activity, trauma, and allergic reactions [5]. In second stage, ANS activity is a resistance to the stressors to protect our body. Final stage can be divided into two possible results from second stage. If the resistance stage succeeds, then final stage will become a recovery stage. Meanwhile, human body builds a resistance of future similar stress and return to homeostasis. Selye argued that this stage adaptation occurs and builds resilience of stress. On the contrary, if resistance stage fails, then human body will move on to an exhaustion stage. This stage is often considered as a stressful situation which is universally accepted in a society. If this stage occurs frequently and stays for a long time, it can make physical or psychological damage on human body [6][7].

1.2 Daily life stress

In daily life, many people are exposed to various stressors like hardworking, studies, financial issues, social relationship etc. If these stressors' intensity is much higher than that of human resistance threshold, then people tend to be vulnerable to have acute stress disorder [8]. Without taking a proper treatment after getting an acute stress disorder for a long time, it can get worse turning into *Post Traumatic Stress Disorder* (PTSD) or *Panic Disorder*. On the other hand, consistent exposure of stress happens for a long time, then it can cause the chronic stress disorder. Chronic stress disorder syndrome can interrupt regular circadian rhythm, headaches and insomnia [9][10].

1.3 Heart Rate Variability

1.3.1 Heartbeat recording

There are two common ways to measure heartbeat recording. First method is electrocardiogram (ECG) recording [11]. This measuring method is detecting electrical activity from the heart. When measuring ECG data, electrodes attached on the skin. These electrodes detect the electrical changes from the activity of cardiac muscle depolarization followed by repolarization in each heartbeat.

Second measuring method is photoplethysmography (PPG) recording [12]. This method using blue and red color light reflection from human skin. Each heartbeat, the color of blood vessel is changed slightly. Both different light color reflected differences, and sensor detected the changes of each heartbeat. This difference of reflected light power contains heartbeat data and blood oxygen saturation (SpO_2) [13].

1.3.2 Time domain HRV feature

Time domain HRV analysis method was used SDNN, RMSSD and pNN50 features. First the SDNN is standard deviation of N-N interval. N-N interval means normal to normal R-R interval at ECG signal QRS complexes. In PPG signal, the R-R interval can be referred to as a systolic peak to systolic peak. The detailed formula is shown equation (1)

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=2}^{N}[I(n)-\bar{I}]^2} \qquad \text{Eq. (1)}$$

At equation (1), N means the total heartbeat, $I(n)$ n^{th} heartbeat to heartbeat interval and $\bar{I}$ is the average of heartbeat values.

Second method, RMSSD means root mean square of successive N-N interval differences. This method is more focused on the differences between adjacent N-N intervals. The detailed formula is shown equation (2).

$$RMSSD = \sqrt{\frac{1}{N-2}\sum_{n=3}^{N}[I(n)-I(n-1)]^2} \qquad \text{Eq. (2)}$$

Last method, pNN50 is the number of successive intervals that differ by more than 50ms. That means adjacent inter-beat interval (ISI) differences over 50ms ratio of all recorded inter-beat intervals.

1.3.3 Frequency domain HRV feature

Heart rate data records time series. For transferring time domain data to frequency domain data, fast Fourier transform (FFT) [14], autoregressive model (AR) [15], short-term Fourier transform (STFT) [16] or wavelet transform. Short-term Fourier transform and wavelet transform are time-frequency domain analysis that it is suitable for long-term heart rate data in frequency domain analysis.

The spectral features used in frequency domain HRV analysis reside in frequency range. There are three features exist in frequency domain analysis: very low frequency (VLF) range is 0~0.04 HZ, low frequency (LF) range is 0.04~0.15Hz, and high frequency (HF) range is 0.15~0.4Hz. LF band power implicates the SNS and HF band power relates with the PNS activity. Therefore, the ratio of LF and HF power ratio shows the ANS activity can be interpreted of the stress level [17].

1.4 Goal of research

Final goal of this research is implementation stress prediction based on HRV analysis and home healthcare system. In this system, it can be divided three steps. First step is making stable wrist-band type wearable sensor and smartphone application Bluetooth wireless connection, real-time PPG data streaming in smartphone application and storing streamed data into smartphone storage. Second step is processing stored data for predicting stress level. In this step, remove artifact of PPG data, extract HRV features for prediction stress level, and sending data to IoT system for control home appliances. All algorithm is targeted in mobile platform. Characteristic of mobile platform, there are limitation in computing unit performance limit, memory capacity, and limitation of power supplication. For solving computing unit and memory resource issue, I made algorithm has light computing complexity. For improvement of application energy consumption, focused on the wireless connection between application and wrist-band type wearable sensor.

2 Experiment

2.1 Experiments

2.1.1 Participants

In this study, there were 8 people participated in this experiment. 8 participants are university undergraduate and graduate students. Participants consisted that 2 females, and range of age is 21 ~ 25 years old. Also, all participants have no history of cardiac diseases and psychological treatment.

2.1.2 Experiment equipment

The Photoplethysmography (PPG) signal of each participant data was recorded using wristband-type wearable sensor (E4, Empatica, Inc. USA) and in-house iPhone application for data acquisition. E4, wristband-type wearable device has PPG sensor, galvanic skin response (GSR), accelerometer (ACC), and skin temperature sensor. All measured data from these sensors could transmit via Bluetooth low energy (BLE) connection.

In-house iOS application's main function was to store streamed data, participant's student ID number, and start time of each data recording trial at iPhone internal storage. This application developed based on Empatica developer iOS software development kit (SDK) package for streaming data and time stamp from E4 sensor and iOS-specific integrated development environment (IDE) Xcode version 9.3.1 (Apple, Inc. USA) implemented on *objective-c* language. Therefore, all participants installed in-house iOS application their own iPhone and connected with E4 sensor. In-house application's main function was to store streamed data in iPhone storage.

2.1.3 Experiment procedure

Participants recorded PPG data for 30 seconds, 3 times at each recording time (at 12:00, 18:00, and 10 minutes before sleep). According to Salahuddin et al. [18], 30 seconds recording heartbeat data based HRV analysis can provide a meaningful indicator of mental stress. And at the end of the day, participant self-estimated own stress level with perceived stress scale [19] (PSS) questionnaire. The PSS questionnaire what in this experiment used was modified for this experiment that original PSS-10 questionnaire's stress measurement period is one month but, modified PSS questionnaire's stress measurement period is one day. And also, all questionnaires were translated in Korean language (PSS-10 Korean). Figure 1 is the modified PSS questionnaire what was used in this experiment.

지각된 스트레스

다음의 문항들은 각 질문과 관련지어 오늘 하루 동안 당신의 느낌과 생각에 관해서 묻습니다. 각각의 경우, 어떤 방법이든 당신이 얼마나 자주 느끼거나 생각했는지를 정확하게 표시하십시오.

항목	0 전혀없음	1 거의 없음	2 가끔	3 자주	4 매우 자주
1. 오늘 하루 동안 당신은 뜻밖에 일어난 일 때문에 얼마나 자주 노여워했습니까?	0	1	2	3	4
2. 오늘 하루 동안 당신은 당신의 삶에서 중요한 것들을 조절 할 수 없다고 얼마나 자주 느꼈습니까?	0	1	2	3	4
3. 오늘 하루 동안 당신은 얼마나 자주 신경질이 나고 스트레스를 받았다고 느낍니까?	0	1	2	3	4
*4. 오늘 하루 동안 당신은 얼마나 자주 당신의 개인적인 문제들을 처리할 수 있는 능력에 대해서 자신감을 느꼈습니까?	0	1	2	3	4
*5. 오늘 하루 동안 당신은 얼마나 자주 일이 뜻대로 잘 되었다고 느꼈습니까?	0	1	2	3	4
6. 오늘 하루 동안 당신은 얼마나 자주 당신이 해야 할 일들에 대처할 수 없다고 깨달았습니까?	0	1	2	3	4
*7. 오늘 하루 동안 당신은 삶 속에서 짜증나는 것을 얼마나 자주 조절 할 수 있었습니까?	0	1	2	3	4
*8. 오늘 하루 동안 당신은 얼마나 자주 모든 일들을 잘 관리했다고 느꼈습니까?	0	1	3	3	4
9. 오늘 하루 동안 당신은 당신이 조절할 수 없는 일들 때문에 얼마나 자주 화가 났습니까?	0	1	2	3	4
10. 오늘 하루 동안 당신이 이겨낼 수 없는 어려움들이 너무 높게 쌓인다고 얼마나 자주 느꼈습니까?	0	1	2	3	4

PSS-10 Korean translation courtesy of Dr. Gwi-Ryung Son Hong,
Hanyang University, South Korea. March 12, 2012

Figure 1. Modified the PSS-10 Korean questionnaire were used in this experiment. Original PSS-10 questionnaire stress measurement period is 1 month or 1 week. But fit in the purpose of this research, period of stress measurement was changed to 1 day.

3 Data Analysis

3.1 Preprocessing PPG signal

PPG sensor detects blood volume pulse via red and blue color light reflection, that it is vulnerable to artifact caused by various condition. Therefore, I asked to experiment participants sit down on chair and do not move during the recording PPG data. Despite these efforts, there were lots of artifacts in the PPG signal. Due to this reason, it is important to remove the artifact of the measured PPG data from wearable sensor for estimating accurate heart rate variability analysis. In PPG signal contains the 'Systolic Peak' and 'Diastolic Peak' components. When extracting HR data from PPG signal, only uses Peak-to-Peak interval value (systolic peak to systolic peak) such as figure 2. Therefore, in preprocessing of the raw PPG signal main goal was removing artifacts and diastolic peak value.

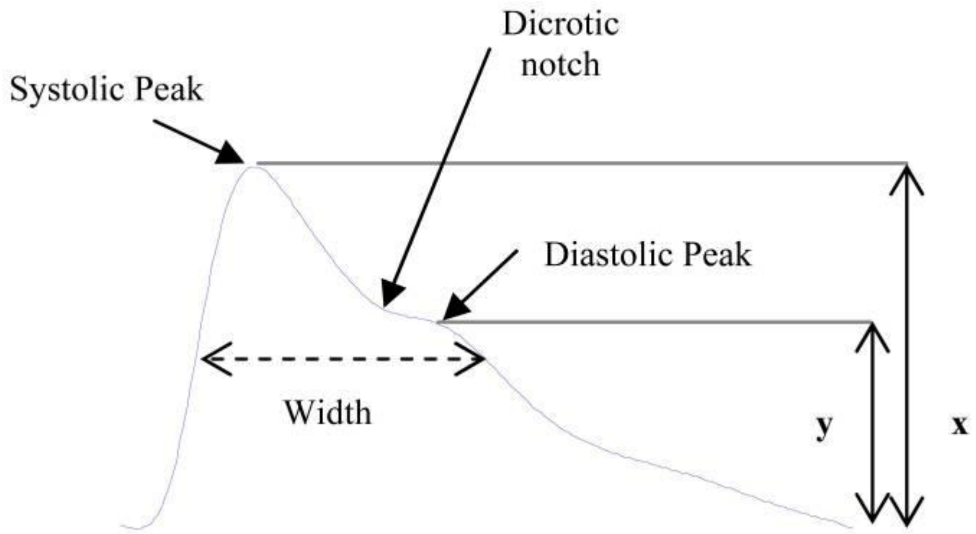


Figure 2. Illustration of PPG signal. In this figure explain about systolic peak, dicrotic notch, and diastolic peak components in PPG signal. 'x' and 'y' value of this figure represents to systolic peak and diastolic peak amplitude value. Inter-beat interval (IBI) calculate systolic peak to systolic peak duration time. IBI data represents to HR. This figure is from Elgendi et al. [20] paper, Fig (9).

PPG analysis algorithms were implemented with C++ language with 'GNU Compiler Collection (GCC)' 4.2.1 version. The key algorithm 'multi-level bandpass filtering' used for removing artifact. The main purpose of multi-level bandpass filtering is removing artifact and making signal easy to detect peak.

Multi-level bandpass filtering is a hierarchical bandpass filtering that is consisted of 3 different bandpass filters. The first bandpass filter passed signals within 0.5 ~ 11Hz, and second bandpass filter is passing 0.8 ~ 3Hz range signals. The last bandpass filter has more narrowed range to pass 0.9 Hz ~ 1.6 Hz signals than other two bandpass filters. Figure 3 illustrates a comparison about multi-level bandpass filtering results and single bandpass filtering with 0.9 ~ 1.6 Hz range. As the result of the comparison, single bandpass filtering also reduces the artifact of the signal, but still diastolic peak signal contains the preprocessed signal. Diastolic peak is one of the components from the cardiovascular system, but I decided to get rid of it because it can lead to inaccurate results when measuring the heart rate. As that aspects, multi-level bandpass filtering is more suitable algorithm in extracting HR information.

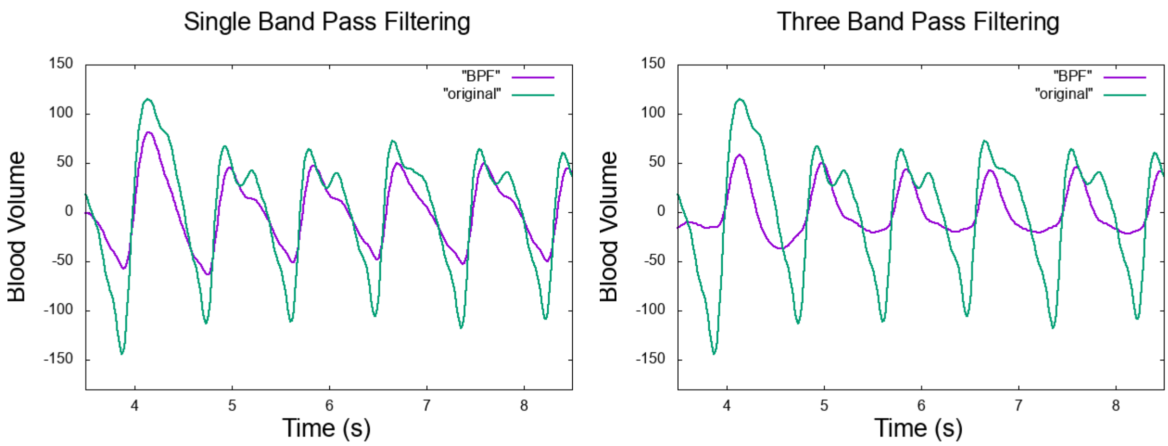


Figure 3. Left figure is about single band pass filtering PPG data with 0.9 ~ 1.6Hz signals. Right figure is multi-level bandpass filtering results. This figure is one of the parts of the participant's signal preprocessing results. As the result of signal processing, multi-level bandpass filtering is more efficient that remove artifact and diastolic peak. This figure is result from C++ based implementation algorithm results and plotting program was used in 'gnuplot' at LINUX, Ubuntu 14.0.2 LTS version open source basic package.

3.2 Peak detection algorithm

After the preprocessing raw PPG signal data, peak detection step is most important part of extract HR data from filtered PPG data. In traditional peak detection algorithm, 'Automatic Multi-Scale Peak Detection algorithm (AMPD)' which is proposed by Felix *Scholkmann et al*. [21]. However, in this study's purpose is the mobile environment application implementation, which is analyzing raw PPG data from wearable sensor, and as fast as possible to shows the result of user's daily stress level. Therefore, I focused on this limitation of the mobile application build environment, I suggested that window shifting and score-based detection algorithm. First, the AMPD algorithm calculating about local maxima scalogram (LMS). This calculation has to make a $L \times N$ matrix (N is the length of the signal and L is the moving window size) and it must be use $O(n^2)$ complexity and memory consumption. After that calculation, calculate each signal which are inside of windows converts to frequency domain. In this step, algorithm complexity is $O(n\log(n))$ when it used 'Fast Fourier Transform (FFT)', and memory consumption is $O(n)$ of each window. As a result, AMPD algorithm has totally $O(n^3\log(n))$ computation complexity and $L^2 \times N$ size of memory consumption. AMPD algorithm has large complexity in calculation process. Suggested window shifting and score-based peak detection algorithm is focused on this calculation complexity aspect improvement.

Window shifting and score based peak detection (WSSPD) algorithm, the window size was varied from 1.5 to 0.5 second. The initial window size is 1.5 seconds and shifting the windows to end of the data to find the highest peak point. Each highest peak time point gets one score in every iteration. After each iteration the window size decrease 0.1 second until it become 0.5 second. Therefore, there are 10 different size of window exists. After the all size of window shifting was finished, the each detected peak time point get score and using that stored score finalize peak detection as following procedure.

1) Find the highest score peak time point.
(Multiple peak points can be included if they have same points.)
2) Calculate interval between each peak point.
(If there is only one peak point detected this step will be skipped.)
3) If the interval is larger than 1.5 second, find the highest point in interval.
4) Otherwise, the interval is less than 0.5 second, then exclude from the peak point.

5) Repeat **1 ~ 4)** procedure ascending iteration and descending iteration.

After finalize the window shifting and score based peak detection algorithm, peak to peak data values represent inter-beat interval (IBI) data. Window shifting and score based peak detection algorithm has a $O(n^2)$ computation complexity and $L + N'$ memory usage. *N'* is all detected local maxima peak value. Therefore, this algorithm is much faster and using less memory usage during an execution than AMPD algorithm.

3.3 HRV Feature Extraction

In this study, experiment participants recorded PPG data 30 seconds. In short term recorded heartbeat data analysis, time domain HRV SDNN method does not achieve a consensus with mental stress according to *Salahuddin et al*., [18]. *Wang et al*., [22] introduces LF/HF feature and SDNN/RMSSD are highly correlated with the mental stress, but this result is from over 3 minutes ECG signal recording data analysis. Therefore, frequency domain HRV feature LF/HF is more appropriate in this study, so that I applied this feature to estimate a stress level.

In frequency domain HRV feature, LF and HF value were used. LF is 0.04 ~ 0.15Hz range power and HF is 0.15 ~ 0.4Hz range power value. Both feature frequency range is too small that fast Fourier Transform (FFT) can suffer from spectral leakage effects due to the windowing [23]. As that reason, I used the autoregressive (AR) model which shows better transform resolution rather than FFT method. AR model

$$y(n) = -\sum_{k=1}^{p} x(k)y(n-k) + w(n) \qquad \text{Eq. (3)}$$

where $x(k)$ denotes AR coefficients, $y(n)$ is HRV data, and $w(n)$ is the white noise at time n.

All experiment participants recorded PPG data 3 times in the same day. I calculated LF/HF feature each 3 times recording data and average of these 3 features was used in daily mental stress prediction.

3.4 Daily mental stress prediction

One of this study goals was to show users how much mental stress they had on a scale of 0 to 40, rather than just notice them how high or low the mental stress is. For achieve this goal, linear regression method is fitful in this study. Prediction accuracy was evaluated by leave-one-out validation. Prediction accuracy was calculated equation (4).

$$Accuracy\ (\%) = \left[1 - \left|\frac{\left(x_{coeff} \times test_{LF/HF} + y_{coeff}\right) c test_{PSS}}{PSS_{max}}\right|\right] \times 100 \qquad \text{Eq. (4)}$$

where x_{coeff} and y_{coeff} are trained linear regression model coefficients. $test_{LF/HF}$ is LF/HF test data value and $test_{PSS}$ is test PSS score. PSS_{max} is the possible maximum score that is always 40. Figure 4 illustrate the result of linear fitting. The average correlation coefficient of all participants was 0.64.

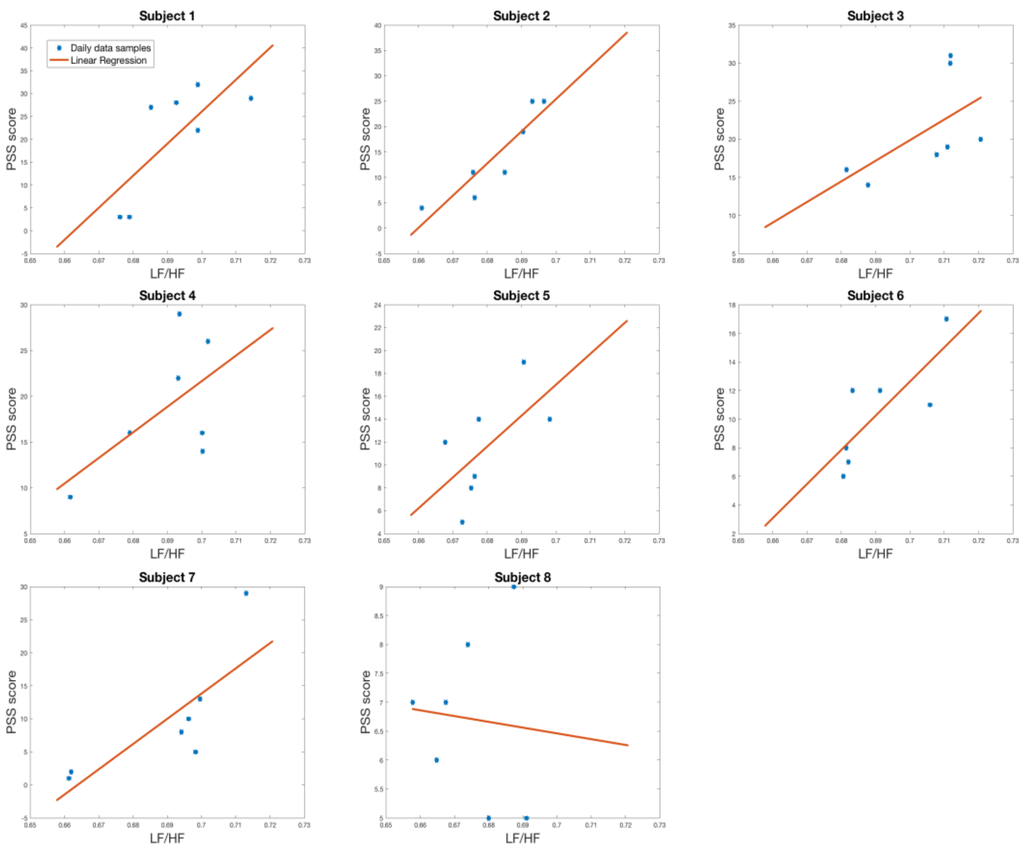


Figure 4. This figure is the results of each participant's HRV LF/HF feature value and PSS score linear fitting results. Except for the 8th participant, PSS score and LF/HF feature proportional relationship.

4 Results & Application

4.1 Mental stress Prediction

Mental stress prediction algorithm uses linear regression model. This model is trained by calculated LF/HF value. Prediction model evaluation method was used leave-one-out validation. When evaluation of this prediction model, each participant's HRV value is different that it is hard to use another participant's HRV data for predicting mental stress. Therefore, I was used same participant's HRV data set to train prediction model and testing for evaluating the prediction validity.

The result of all subject's stress prediction accuracy average value is 86.35%. Figure 5 is the result of comparing the 7-day responded PSS value and the prediction result by each day.

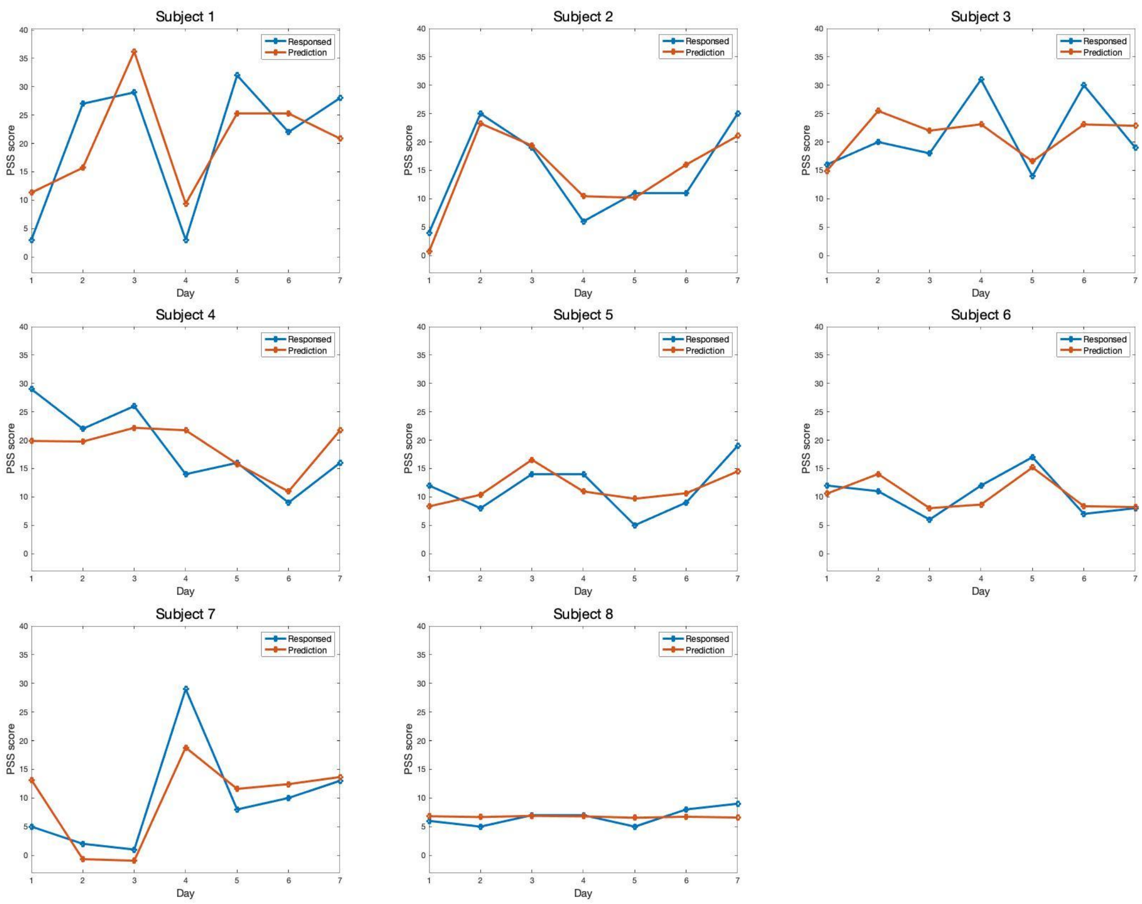


Figure 5. This figure is comparison of participant's each day responded PSS score and prediction model result of each date. Blue line is the responded PSS score value and red line is the prediction results.

As result of figure 5, the PSS response of the 8th participant was not able to build a prediction model, because continuous response without significant change for 7 days.

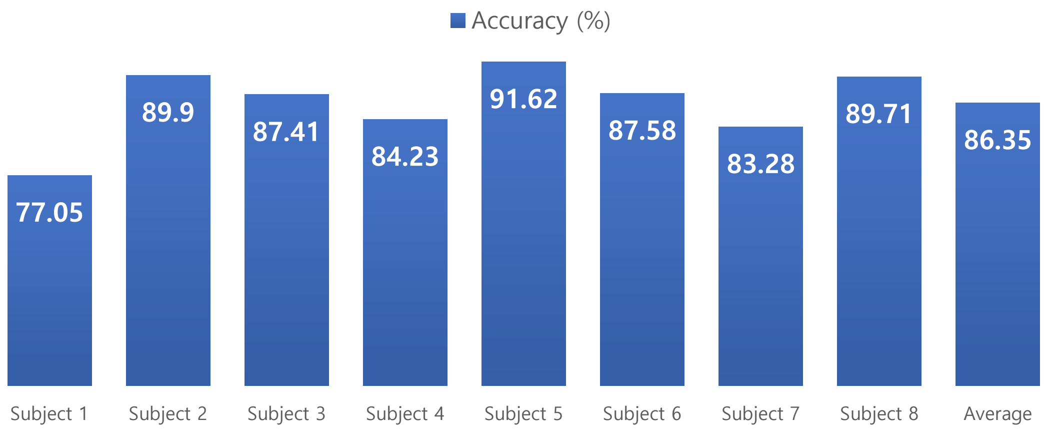


Figure 6. This figure illustrates the result of each participant's mental stress prediction.

Figure 6 shows the average accuracy of each participant 7 days prediction result.

Comparing the result of suggested multi-level bandpass filtered and single bandpass filtered PPG data use in same prediction algorithm, single bandpass filtered PPG data prediction accuracy is 78.92% which is lower than multi-level bandpass filtered PPG data stress prediction. Due to the single bandpass filter cannot remove all diastolic peak in PPG data, therefore WSSPD makes error in peak detection. These results make lower accuracy.

4.2 Applicate mental stress prediction method in home IoT system

PSS values reflect figures for stress in daily life. In addition, since these PSS values were predicted HRV analysis, I built a scenario for an IoT based home healthcare system that can be used in real life. The idea of is described in figure 7. It is a healthcare system that uses home appliances connected with IoT so that user can take a rest at home based on user's daily stress level when user come homme after finishing own daily schedule. For building this scenario, I developed smartphone application that real-time streaming and storing data into internal storage in smartphone. This application basic function is focused on the preparing unstable connection during the measuring PPG data, less power consumption, and supporting background PPG data streaming.

First, wireless connection is often unstable because of interference from radio communication and connection distance. Therefore, I developed PPG data streaming application monitoring the connection status and based on the connection status, automatically stop or resume data acquisition. In case of unstable connection, application is designed to measure PPG data again from the beginning. Figure 8a shows the streaming application was designed for iOS environment. And figure 8b illustrates the controlling home automation system via internet communication with sensor node (Sensor Node, Hanbit EDS, Inc. Korea).

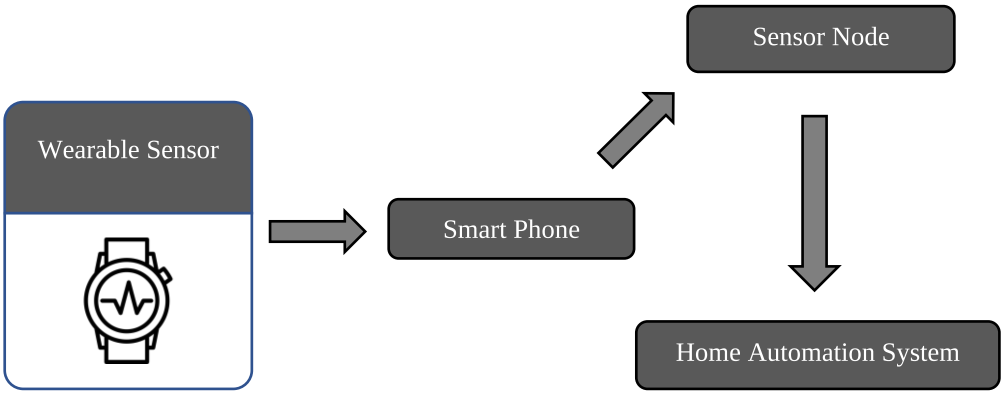
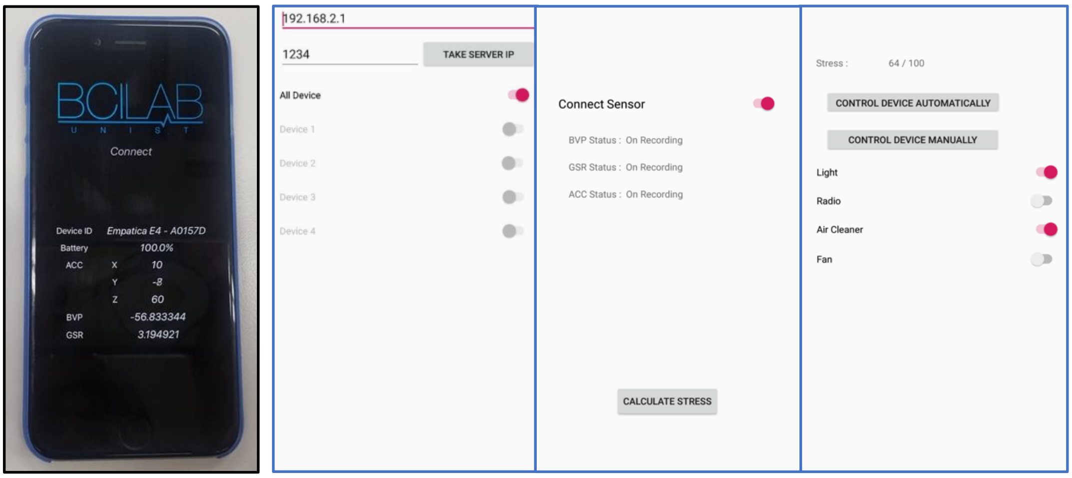


Figure 7. It is a healthcare system that uses home appliances connected with IoT platform scenario. Wearable sensor transmits PPG data to smartphone. After the transmission, smartphone application calculates the HRV data and evaluate stress level (PSS score). Stress evaluation has been finished, application recommends the home appliances setting. Also, user can customize the home appliances setting at each stress level. User chosen home appliances setting condition transmitted sensor node. At this transmission method uses internet user datagram protocol (UDP) communication. Therefore, if smartphone connected Wi-fi or mobile data, then user can control home appliances in anywhere. Sensor node directly controls home appliances. This scenario has a purpose of as possible as giving opportunity to best taking a rest.

Seoncd, in smartphone operating system (OS) environment, application's computation complexity and memory consumption is directly affect on the electricity usage. Also this application uses wireless connection. So that I focused on the algorithm optimization for reduce energy consumption. In Blueetooth connection with wearable sensor, there are lots of Bluetooth commuication specification, I used 'Bluetooth Low Energy (BLE)' communication method.

Third, PPG data recording duration is 30 seconds. In this time, user can feel boring only stareing phone screen without any movement. So that, I designed streaming application working on a background process, that make possible use other



(a) (b)

Figure 8. (a) is the wearable sensor streaming iOS platform application. This application streaming real-time data from wearable sensor recorded. Wearable sensor gives device ID, battery status, accelerometer data, Blood volume pressure (BVP, this data as same as PPG data) and GSR data. (b) is implemented in android OS environment. There are three captured screens in the figure 8(b). First screen function is taking sensor node IP address and port number for internet connection. Below switches are for testing connection. Second screen is connecting with wearable sensor. This screen shows the recording status and 'calculates stress' button is the start stress predicting algorithm. That button activated when the recording data from the wearable device has been finished. Last screen is control home appliances based on predicted stress. 'Control device automatically' button has function is controlling home appliances default setting. 'Control device manually' button makes can store the home appliances control setting

application at the recording time. Also most of smartphone application processor (AP) has mutiple processor core and it devided in main processor and background processor. Application background work uses background processor in AP. This processor has lower performance, but less power consumption than main processor. However, BLE communication data streaming does not need much computing resources that it is suitable to operate in background.

5 Discussion

5.1 Released similar services

'Samsung Health' application (Samsung, Inc. Korea) supports to measure *Beat per Minute* (BPM) data and according to that BPM data it measures the stress level ranging from 0 to 100. When users measure BPM data from Samsung smartwatch PPG sensor this application fails to explain how the stress level is measured and proper reference about the stress levels. Also, this application doesn't provide IoT services, only to give the history of previous measured stress level results and record the stressor diary.

Implemented system in this study has a purpose to provide users with information which offers users criteria of stress levels. Because this specific reference of stress measured value can give trust to users. In addition to that this stress measuring result is used to control home appliances in order to make it efficient to relieve the stress level.

5.2 Comparing other Bio-signals in measuring stress

This algorithm only uses PPG data. However, many other bio-signals from human body use stress level measuring. For example, *Villarejo et al*. [24] and *Bakker et al.* [25] study use GSR and *Vinkers et al.* [26] study uses body temperature and cortisol concentration [27] also can use measure stress level, because GSR and body temperature sensor are also built in many wearable devices. GSR data and human body temperature react to the very moment of stressful situation. However, after the reaction of stress, GSR and body temperature are recovered to the normal states. With this reason, both bio-signal based stress detection systems have to be turned on all day long. That means, wearable device and smartphone application should be activated for a long time. This long activation takes lots of energy consumption, so wearable device and smartphone battery will be discharged rapidly. On the contrary, even a few minutes of recorded PPG data can be used in measuring stress level. Cortisol concentration can also be used in measuring stress level. Cortisol sample can be obtained from saliva. But it is inconvenient to collect saliva in a daily life. With these reasons, HRV analysis is one of the most simple and effective ways to measure stress levels.

Also heartbeat can be measured from ECG. Already released wearable ECG products exist in the market. For example, Apple watch 5 (Apple, Inc. USA), and QardioCore Wireless ECG monitor device (QARDIO, Inc. USA) are wearable devices. Previous version of Apple Watch series uses PPG sensor. New version of Apple Watch 5 supports ECG data recording. This device was approved from US Food and Drug Administration (FDA) as a clinical device. Apple Watch 5 can be applicated in this system, but because of Apple's own privacy regulations developer cannot access to the raw ECG data. Owing to that limitation, when Apple Watch 5 is applied in stress prediction and home healthcare system, developer can only use the processed data by Apple. On the contrary, QardioCore wireless ECG monitor device gives full raw data to developer making it easy to use. This device is a bandage type which should be worn around the chest, so it makes inconvenient for the users.

5.3 Application in psychological treatment

Developed system in this study can be applied to the acute stress disorder, panic disorder and PTSD patients. These diseases are caused by severe stress. Especially panic disorder patients do not realize the fact that they have such a disease at the first time. Usually these patients go to hospitals for other symptoms, because they think that there is something wrong with other organs in their body. For that reason, implemented system can help those people with giving stress level feedback and suggesting going to the doctor. This feedback system can be very helpful to the patients who are under treatment. If patients could be informed about arousal status at each recording time, then the patients would be able to get feedback easily and get informed about the progress of treatment. Also, this feedback system gives patients motivation to concentrate on the treatment. It is important for patients to participate in psychiatric therapy steadily.

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